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The effects of projected climate and climate extremes on a winter and summer crop in the southeast USA

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ABSTRACT

In this study, we explored how changing climate conditions in the 20th and 21st century affect summer and winter crop yields the southeast United States. An ensemble of 10 global circulation models (GCMs) were utilized and the uncertainties associated to their estimates were calculated. The objectives of this study were to utilize historical and projected climate data to (*i*) analyse historical and projected precipitation and temperature separately for a winter and a summer crop; (*ii*) evaluate how these climate factors impact the crop yield and the water use; (*iii*) quantify for the two crops, and for vegetative vs. reproductive stages, the impacts of climate extremes on crop yield and water use. The daily weather data for both historical and projected periods were obtained from the Multivariate Adaptive Constructed Analogs (MACA) downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) datasets. A series of 16 climate extremes indices mostly selected from the Expert Team on Climate Change Detection and Indices (ETCCDI) was calculated using the MACA downscaled CMIP5 data. The Decision Support System for Agrotechnology Transfer (DSSAT) model was used to simulate the effects of climate on a summer crop (maize, using the CERES-Maize model) and a winter crop (wheat, using the CERES-Wheat model) crop on a silty-clay and on a sandy soil during the historical baseline (1950–1999) and the projected (2006–2055) periods. Overall, the decadal crop-specific growing season temperature trend showed warming of the southeast with little variability across the climate models for the baseline and an increase uncertainty for future conditions. For each 1 °C the simulated maize yield would decrease by 4.6% across the different climate projections, while wheat would be reduced by 3.8%. Water use efficiency decreased under future projections by 2.7% on a silty-clay soil, independently of the winter/summer crop, but on a sandy soil the decrease was 4% for maize and 1.7% for wheat. The impacts of projected temperature and rainfall change will be different for a winter than for a summer crop depending on the type of soil on which the crop is grown.

1. Introduction

The rapid increase of world's population and its projected trend associated with an increase in global food demand make agriculture to face a dilemma of producing more food on the same (or even less) cultivated areas (Foley et al., 2011). Failing to match food production with the global food demand might cause increase in food prices leading to an increase in poverty rates and hunger (Godfray et al., 2010). In addition, crop production should be obtained in a sustainable way that is without polluting the environment but without reducing the farmers' income.

Agriculture is very sensitive to both climate variability and change and therefore any adverse impact due to climate will increase the vulnerability of agricultural production. The growing season (defined as the period between sowing and harvest) temperature, rainfall, and the CO_2 concentrations affect positively/negatively crop growth and development. Many studies have been conducted assessing the effects of individual climate parameters, or a combination of them on crop growth, development, and yield (Amthor, 2001; Sadras and Monzon, 2006; Kimball, 2010; Allen et al., 2011; Hatfield et al., 2011). The southeast USA has a very heterogeneous crop production and agriculture is among the major economic contributors to the region contributing to more than 17% the total annual USA agricultural production (Ingram et al., 2013). The projected future changes of droughts, and heat stress during summer months will affect agriculture outputs in the region (Ingram et al., 2013).The climatic effects on crops can be quantified using crop growth models (CSM) as they simulate the daily growth, development and final yield as affected by weather, soil, crop characteristics, and agronomic management; and CSM can be used to extrapolate such interactions beyond a single year and a single

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experimental site (Jones et al., 2003).

Global Climate Models (GCMs) have been used to study the impacts of projected climate for a specific agricultural area. Their resolutions are rather coarse and to provide a better application to local conditions they have been downscaled at finer scales using either a statistical or a dynamic downscaling (Fowler et al., 2007). However, GCMs might contain biases in terms of specific temperature extremes or rainfall patterns that could affect their use in CSM and bias the simulated yield (Cammarano et al., 2013; Carbone et al., 2003; Hansen and Jones, 2000). Nevertheless, when a sufficient big ensemble of GCMs are used as input into the CSM the problem of bias due to a single or few GCMs would be minimized because the uncertainty around such estimates can be quantified (Tebaldi and Knutti, 2007).

Karmalkar and Bradley (2017) pointed out that the estimated impacts of temperature will change according to the level of resolution studies, e.g. from the globe to regional. For climate studies related to agricultural production the three main issues to consider when analysing the impacts of climate on crop production are: (i) the scale (global vs. local); (ii) the growth stage of the crop, because some temperature threshold might be harmful at a particular stage but not at another; and (iii) the time-frame (annual vs. growing season) because it would be more useful to look at the growing season climatology rather than the calendar year. The latter point means that winter and/or summer crops will be impacted differently by climate variability and climate change. Folberth et al. (2016) showed that the type of soil can outweigh and buffer the effects of climate variability like changes in rainfall and temperature. Their study was done at a global level and they concluded that any recommendations in terms of adaptations should consider such issue.

The quantification of projected climate impacts on agricultural production are an important step to make when choosing adaptation measures for sustainable food supply. In this study, we will explore how changing climate conditions in the 20th and 21st century affect summer and winter crop yields in the southeast United States on two contrasting soil types. The approach used an ensemble of GCMs and the uncertainties associated to their estimates were determined.

The objectives of this study were to utilize historical and projected climate data to (*i*) analyse historical and projected precipitation and temperature separately for a winter and a summer crop; (*ii*) evaluate how these climate factors impact the production and the water use of the two crops; (*iii*) quantify for the two crops, and for vegetative vs. reproductive stages the impacts of climate extremes on crop yield and water use.

2. Materials and methods

2.1. Weather data

The weather data used in this study were retrieved from the Multivariate Adaptive Constructed Analogs (MACA) downscaled CMIP5 datasets (Abatzoglou, 2011), available at http://maca.northwestknowledge.net/data_portal.php. MACA is a statistical downscaling method which used a training dataset based on observed meteorological data to correct historical and projected biases and match the spatial patterns in climate model outputs (Abatzoglou and Brown, 2012). The MACA method downscaled 20 Global Climate Models (GCM) belonging to the Coupled Model Inter-Comparison Project 5 (CMIP5) on the historical weather data series (1950–2005) and on the future Representative Concentration Pathways (RCPs) 4.5 and 8.5 (2006–2099). The CO_2 concentration considered for each period was 350 ppm for the baseline, 538 ppm and 936 ppm for the RCP4.5 and RCP8.5, respectively. For this study we used the following daily variables: daily maximum temperature (T*max*); daily minimum temperature (T*min*); average daily rainfall (*prcp*); and average daily downward shortwave radiation (*rsds*). This study used the newest version of the MACA downscaled CMIP5 datasets: MACA-v2-METDATA. This dataset has been evaluated with observed data in the southeast USA through the PINEMAP project (PineMAP, 2017). We utilized the dataset for the historical period and the two RCPs, 4.5 and 8.5, respectively. The GCMs chosen were reported in Table 1 along with the associated CO_2 concentration considered for each RCP. The area considered in this study spanned over 5 States located in the southeast USA: Alabama, Florida, Georgia, North Carolina, South Carolina.

Table 1
List of the Global Climate Models (GCMs) used in the study as both historical dataset, RCP4.5 and RCP8.5.

GCM	GCM	Baseline	Representative Concentration Pathways (RCPs)	
ID	#	*Historical*	*RCP4.5*	*RC8.5*
bcc-csm1-1-m	1	350	538	936
CanESM2	2	350	538	936
CCSM4	3	350	538	936
CNRM-CM5	4	350	538	936
CSIRO-Mk3-6-0	5	350	538	936
GFDL-ESM2M_	6	350	538	936
HadGEM2-ES365	7	350	538	936
IPSL-CM5A-MR	8	350	538	936
MIROC5	9	350	538	936
NorESM1-M	10	350	538	936

2.2. Climate indices

A series of 16 climate indices selected from the Expert Team on Climate Change Detection and Indices (ETCCDI, Zhang et al., 2011) was calculated using the MACA-v2-METDATA data (baseline, RCP 4.5 and RCP 8.5). The indices were calculated using daily data and split between sowing to anthesis and anthesis to maturity. This was done to separate the climate effect on the two major phenological stages which were flowering and grain filling. Specifically, the indices dealt with the effects of maximum and minimum temperature, and with the effects of rainfall intensity and duration. The thresholds for T*max* and T*min* used in the calculation of the indices was derived from published results were the effects of daily temperatures affecting crop growth, development and senescence rates on wheat and maize were analysed. For maize, the thresholds were T*min* < 8 °C and T*max* of > 34 °C. The former, caused a halt in maize development, the latter accelerated maize life cycle causing a shortening of grain-filling duration and a stop to crop growth (Lopez-Cedron et al., 2005). For wheat the thresholds were T*min* < 0 °C at which crop development stops and T*max* > 32 °C which caused heat stress and reduction in yield due to acceleration in senescence rates (Asseng et al., 2011; Porter and Gawith 1999). The indices were described in Table 2.

2.3. Crop simulation

The simulation of daily maize and wheat growth and development during the historical baseline (1950–1999) and the projected (2006–2055) periods were made using the DSSAT 4.5 (Decision Support System for Agrotechnology Transfer; Hoogenboom et al., 2010; Jones et al., 2003) CERES-Maize model and CERES-Wheat model, respectively. The DSSAT has been run and tested with experimental data worldwide for more than 20 years resulting in one of the most utilized crop models (Koo and Rivington, 2005). The modelling setup for this experiment is the same as the one described in Cammarano et al. (2013; Cammarano et al. (2013; 2016) and Tian et al. (2015), which has been well calibrated and validated using trial data in the southeast USA. The only difference is that the CERES-Wheat is used instead of the APSIM-NWheat 1.55s, and the crop parameters for the CERES-Wheat were obtained from the work of Tapley et al. (2012). The maize cultivar used in the simulation was a medium season hybrid, while for wheat it was

Table 2
Climate and crop indices utilized in the study.

Climate Indices	Description
SAL	Sowing to anthesis length
AML	anthesis to maturity length
iHD	Number of days above temperature threshold
iLD	Number of days below temperature threshold
iCHD	Maximum number of consecutive hot days
iCLD	Maximum number of consecutive cold days
DTR	Diurnal temperature range
mTmax	Maximum T*max*
mTmin	Minimum T*min*
iRainDay	Number of wet days
sdii	Simple daily intensity index (precipitation divided by wet days)
iWetSpell	Maximum number of consecutive dry days 1 mm
iDrySpell	Maximum number of consecutive wet days 1 mm
pcp10	Number of heavy precipitation (p) when p ≥ 10 mm
pcp20	Number of very heavy precipitation when p ≥ 20 mm
maxpcp	Maximum 1-day precipitation
Crop model output	
Ys1	Simulated yield using soil 1 (Silty-Clay)
ETs1	Simulated water use using soil 1 (Silty-Clay)
ESs1	Simulated soil water evaporation using soil 1 (Silty-Clay)
EPs1	Simulated plant transpiration using soil 1 (Silty-Clay)
Ys2	Simulated yield using soil 2 (Sandy)
ETs2	Simulated water use using soil 2 (Sandy)
ESs2	Simulated soil water evaporation using soil 2 (Sandy)
EPs2	Simulated plant transpiration using soil 2 (Sandy)

the cultivar Baldwin. For detailed information on model calibration and validation, please refer to Cammarano et al. (2013). We utilized two soil types representative of two common contrasting soils in the southeast USA, a Silty-Clay soil (Soil 1: S1) and a Sandy soil (Soil 2: S2); each soil was run with all weather data. The models were first run as a "potential" in which all the stresses and dynamic interactions between plant and soil are switched off. This follows the Wageningen approach of potential production simulation (van Ittersum et al., 2003). Then, the models were run by turning on the water balance and dynamic but without nitrogen (N) stresses. These two modes of simulation (Potential, and Water stressed) allowed us to separate the effects of temperature from the effects of rainfall.

The effects of CO_2 concentration on simulated yield was evaluated by averaging the 10 GCMs at each location (yielding to 110 individual points). The variability across the GCMs at each location was evaluated using the coefficient of variation, calculated as follows:

$$CV_i = \frac{\sigma_i}{\mu_i} * 100 \tag{1}$$

where the CV is the coefficient of variation for location *i*, σ_i is the standard deviation of the 10 GCMs at location *i*, and μ_i is the mean between the 10 GCMs at location *i*.

The proportion of simulated yield with water stress relative to the potential yield (yield with no stresses) is referred here as Proportional Yield; and it was calculated on both soils (Soil-1 and Soil-2) as follows:

$$Proportional\ \ Yield = \frac{Yj}{YP} \tag{2}$$

were YP is the potential yield, and Y_j is the simulated yield for Soil 1 (S1) and Soil 2 (S2). This calculation was done for the baseline simulations, the RCP4.5 and the RCP8.5.

The simulated yield, water use, soil water evaporation and plant transpiration, for each of the two soils and for baseline, RCP4.5, and RCP8.5 were correlated with the climate indices for both wheat and maize. The Figures showing the correlations were made using the

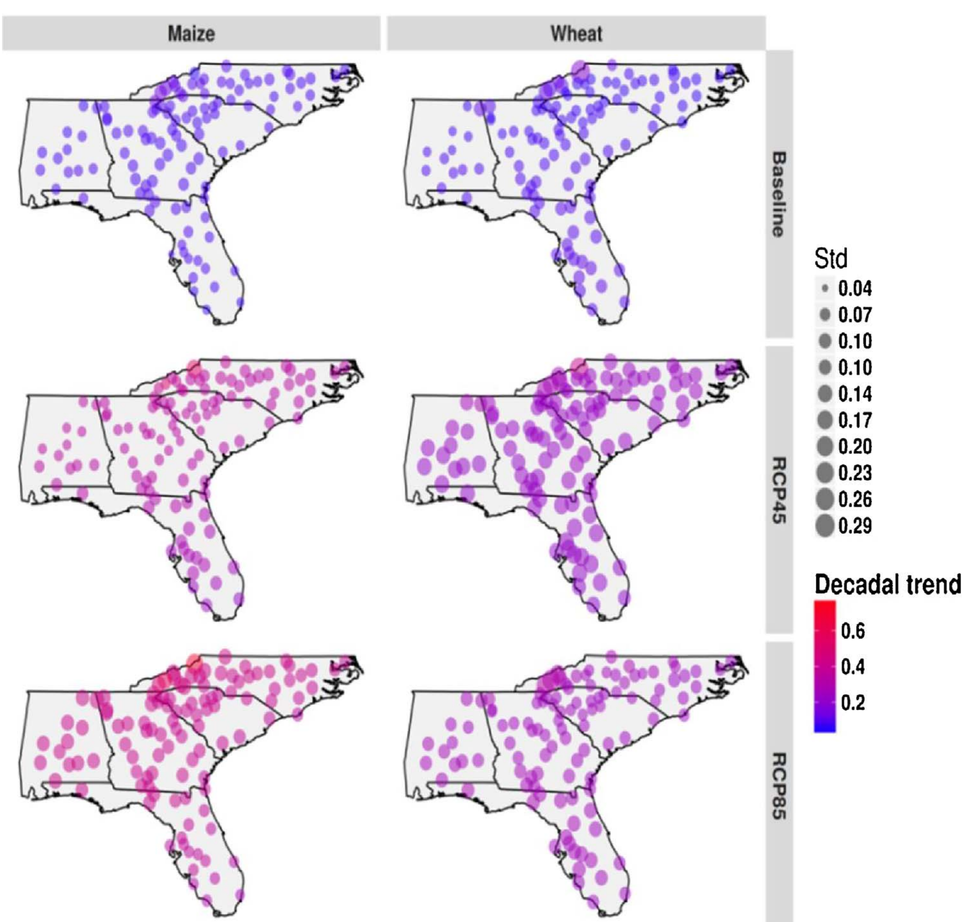

Fig. 1. Decadal trend of the mean growing season temperature for maize and wheat, and for the baseline, RCP4.5 and RCP8.5. The colour of the dots represent the decadal temperature trend, while the size of the dots represents the standard deviation between the 10 GCMs.

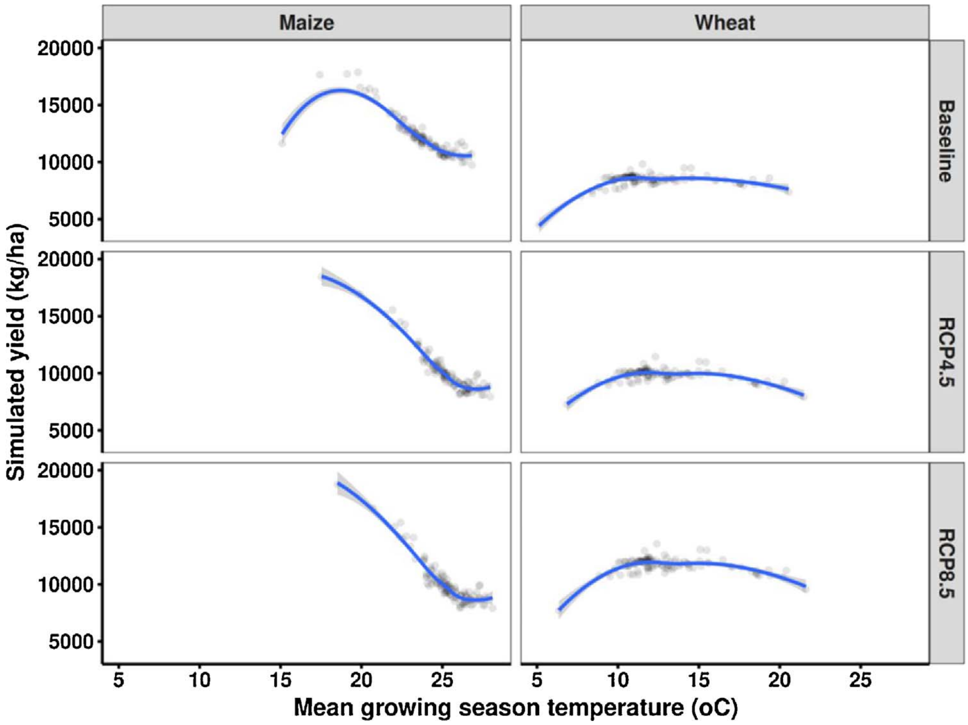

Fig. 2. Relationship between mean growing season temperature and simulated potential yield for maize (right hand column) and wheat (left hand column); for baseline (top row), RCP4.5 (mid row), and RCP8.5 (lower row).

"*corrplot*" package in R (Wei and Simko, 2016).

3. Results

The trend of the mean growing season temperature for the 50 years utilized in this study is shown in Fig. 1 for both maize and wheat and for the baseline, RCP4.5, and RCP8.5, respectively. The colours represent the decadal temperature trend, while the size of the dots represents the standard deviation between the GCMs. For the baseline data, both maize and wheat show mild sign of increase in temperatures, with a decadal value of 0.1 °C per decade (Fig. 1). However, in the northern part of North Carolina a higher decadal trend was coupled with a higher variability among GCMs. At RCP4.5, maize growing seasons showed an increased temperature trend with low variability among the GCMs, while for wheat it was projected a higher decadal trend than maize but with higher overall GCM variability (Fig. 1).

The results of the potential simulation situation, when water and nitrogen routines do not affect growth and yield, are shown in Fig. 2 for both maize and wheat. Overall, potential maize yield decreased as mean growing season temperature increased. For the baseline run, the potential yield peaked at around 19.8 °C with a simulated yield of 17,862 kg ha^{-1} while for RCP4.5 and RCP8.5 potential yield reached 18,400 and 18,700 kg ha^{-1}, respectively (Fig. 2). Wheat did not show any positive response for mean temperature above 10 °C reaching a peak potential yield of 9800 kg ha^{-1}; for the RCP 4.5 and 8.5 the maximum yield was reached at 12 °C with an increase of 16 and 38% respect to the baseline yield, respectively (Fig. 2).

The impact of CO_2 concentration on simulated yield, for each weather station and for the potential production situation is shown in Fig. 3. Overall, simulated maize yield was 17% lower for 936 ppm than with 350 ppm; the simulated wheat yield was 38% higher for 936 ppm than with 350 ppm (Fig. 3). The simulated maize yield varied between each weather station with a range between 7909 and 18,757 kg ha^{-1}. The coefficient of variation (CV) among 10 GCMs at each location was low for the baseline runs, with values ranging between 0.7 and 7%. At RCP8.5 there was a higher variability among GCMs at each location with the CV varying between 3 and 14% (Fig. 3a). The simulated wheat yield did not show the same variability among locations as for maize, with yield values ranging between 4520 and 13,555 kg ha^{-1}. The CV was also lower compared to maize, with values ranging for the baseline between 0.5 and 8%, and the RCP8.5 between 0.4 and 6% (Fig. 3b).

The growing season rainfall for the two crops and for the three different periods (baseline, RCP4.5, and RCP8.5) is shown in Fig. 4. On average, the total growing season rainfall for maize (486 mm) is lower than wheat (563 mm). The baseline data showed that for both maize and wheat there was no divergence in the values of total rainfall between the 10 GCM. However, differences were noticeable at the two RCPs and especially at RCP4.5 for both crops where for maize and wheat GCM-2 and GCM-1, and GCM-8 and GCM-9 diverged from the others (Fig. 4).

The relationship between simulated water use, cumulated at the end of the growing season, and simulated yield considering the plant-soil-water interactions showed a linear relationship for maize while for wheat it reached a peak and then it decreased, independent of the soil type (Fig. 5). For maize, the soil-1 (Clay-silty) was the one that showed the highest yield for the same amount of water use. For each unit increase of water use the yield increased by 16% under soil-1 with respect to soil-2 (Fig. 5). The RCP4.5 and 8.5 showed an increase in yield under both soils. On the other hand, the relationship between water use and yield on wheat was linear up to about 400 mm then it became scattered with a general trend of decreasing yields. And, the RCPs showed the same amount of water use but a higher yield than the baseline, with a mean yield increase of 28% (Fig. 5).

Fig. 6 showed cumulative density curves of the proportional yield respect to the potential yield for the simulations using S1 and S2. Overall, the maize yield exhibited major gaps to the potential production with respect to wheat. For maize, between the baseline and the RCP8.5, and for S1 the maximum values were similar (0.99) but the minimum values of the proportional yield were 0.69 and 0.74 for baseline and RCP8.5, respectively (Fig. 6a). For S2 the maximum values were 0.91 for baseline and 0.94 for RCP8.5, while the minimum values were 0.49 and 0.53, for baseline and RCP8.5, respectively (Fig. 6a). For wheat the proportional yield values were closer to the potential simulations with the maximum values all approaching 1 for both S1 and S2. RCP4.5 showed higher minimum values for S2 respect to the baseline and the RCP8.5 with 0.8, 0.65, and 0.66, respectively (Fig. 6b).

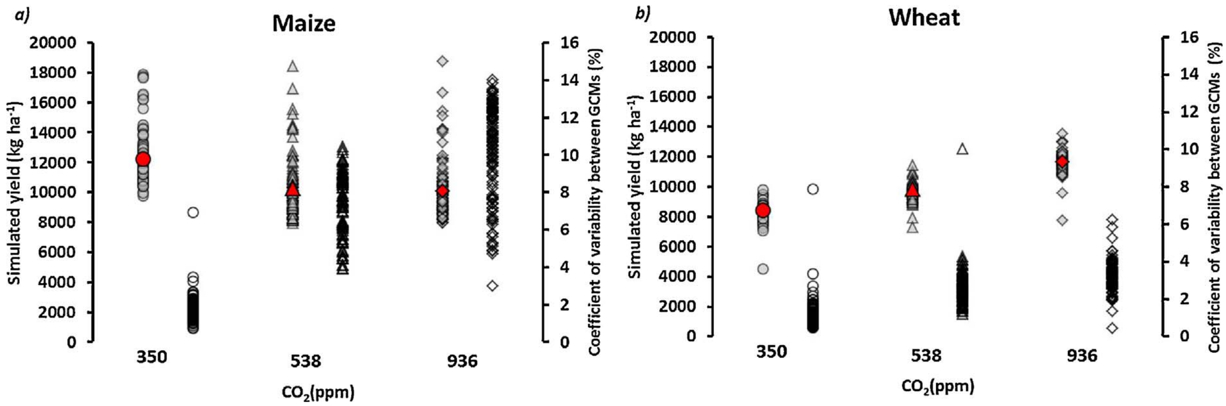

Fig. 3. Simulated potential yields using baseline weather data (grey dots and 350 ppm CO_2), RCP4.5 weather data (grey triangles and 538 ppm CO_2), and RCP8.5 (grey diamonds and 936 ppm CO_2). Each grey symbol represents the mean yield between the 10 GCMs at each location, and the red symbols represent the mean yield across the 110 locations. The empty symbols represent the coefficient of variation between the GCMs at each location. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 7 shows that the simulated yield, soil water evaporation, and plant transpiration using S1 and S2 between sowing and anthesis was negatively correlated with the *iHD, iCHS*, mT_{max}, mT_{min}, and *iDrySpell*. These negative correlations showed values ranging between −0.5 and −0.9, while the $mT_{\max}$ showed the stronger and correlations with the simulated yield, soil evaporation, and plant transpiration, while *iDrySpell* showed a weaker negative correlation between the variables (Fig. 7a). The same period (sowing to anthesis) under the RCP4.5 and RCP8.5 periods showed similar patterns with not tangible increase/decrease in correlations between the crop parameters and the climate indices. However, the *iRainDay* showed increased positive correlations with the simulated crop outputs for the RCP4.5 and 8.5 respect to the baseline (Fig. 7a,c,e).

From anthesis to maturity there was a strengthening of negative correlations between the *iHD, iCHD*, mT_{max}, $mT_{\min}$ and the simulated crop outputs for the baseline run, but the *iDrySpell* showed no or weaker positive correlations with simulated outputs for S1, and only plant transpiration on S2 showed a weaker negative correlation (Fig. 7b). The RCP4.5 and 8.5 showed similar patterns as the baseline (Fig. 7d,f). Stronger positive correlations were obtained for the length between *AML, iLD, iCLD* and the simulated yield, soil evaporation, and plant transpiration for S1 and S2 (Fig. 7).

The correlations between simulated wheat yield (Y), water use (ET), soil water evaporation (ES) and plant transpiration (EP) for the two soils (S1 and S2) is shown in Fig. 8. Overall, from sowing to anthesis, wheat showed negative correlations with mT_{max}, mT_{min}, and *iDrySpell*, and positive correlations with the indices related to number of cold days, and precipitations; with the correlations strength increasing from baseline to RCP8.5 (Fig. 8). In particular, from sowing to anthesis simulated yield on Soil-1 (Ys1) while Ys2 showed some weak positive correlations with iLD, iCLD, DTR, and positive correlations with *sdii* (precipitation intensity index), *iRainDay*, and *iWetSpell*; and Ys2 showed negative correlations with mT_{max}, and $mT_{\min}$ (Fig. 8a). The difference between simulations done under S1 and S2 was that using the second soil (sandy soil) water use, soil evaporation, and plant transpiration showed better correlations with the climate indicators (Fig. 8).

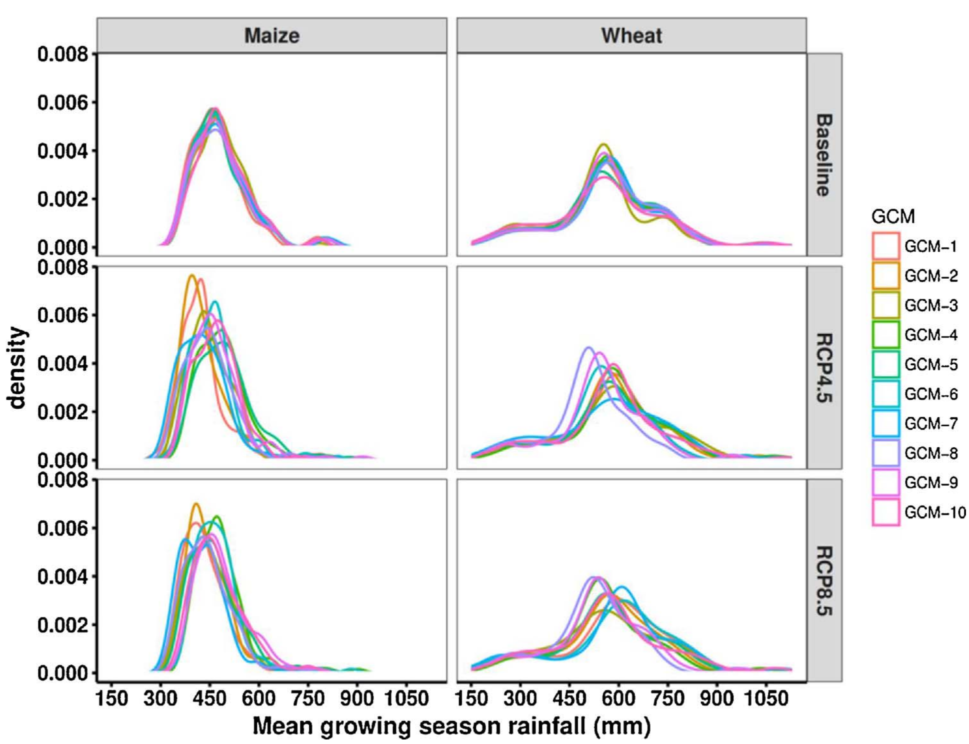

Fig. 4. Density distribution of the total growing season rainfall for maize (right column) and wheat (left column) for the baseline (top row), RCP4.5 (mid row), and RCP8.5 (lower row) for the 10 GCM used in this study.

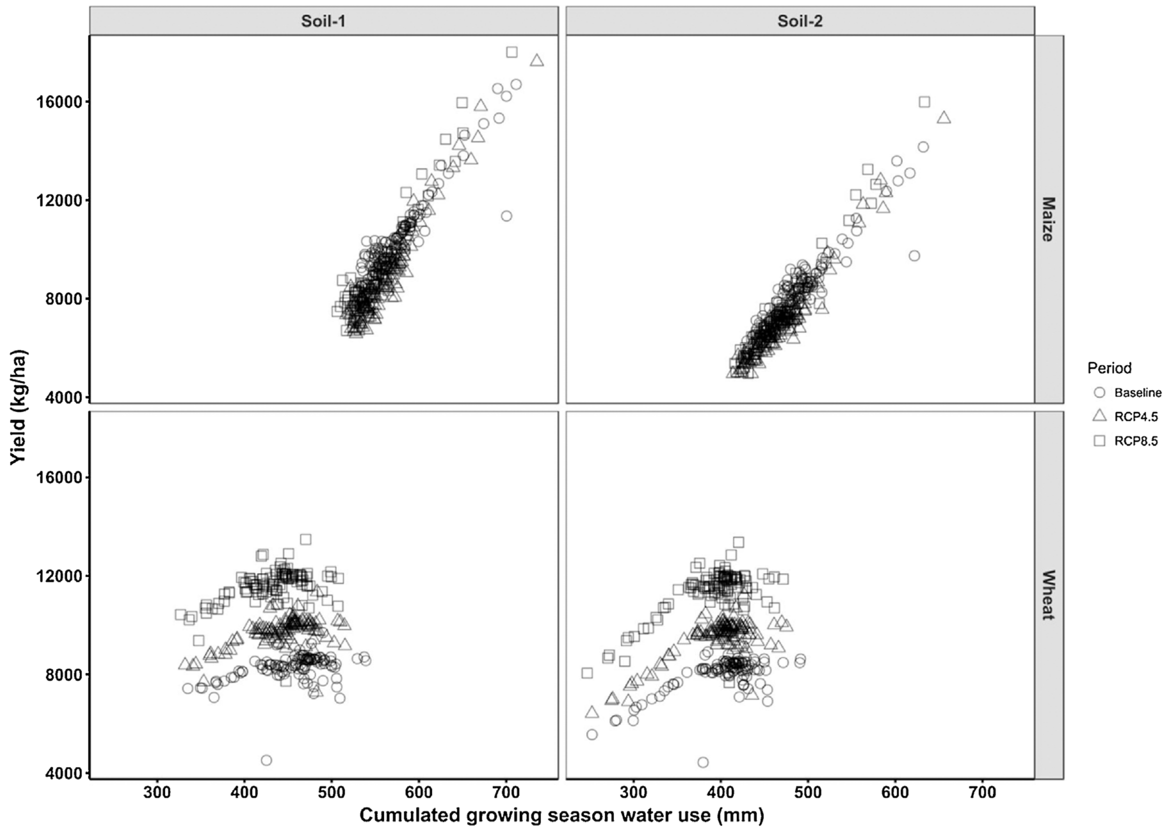

Fig. 5. Relationship between cumulated growing season water use and yield for maize (top row) and wheat (lower row) for the soil-1 (Silty-clay; left column) and the soil-2 (Sandy; right column) for the baseline (open dots), RCP4.5 (open triangles), and RCP8.5 (open squares).

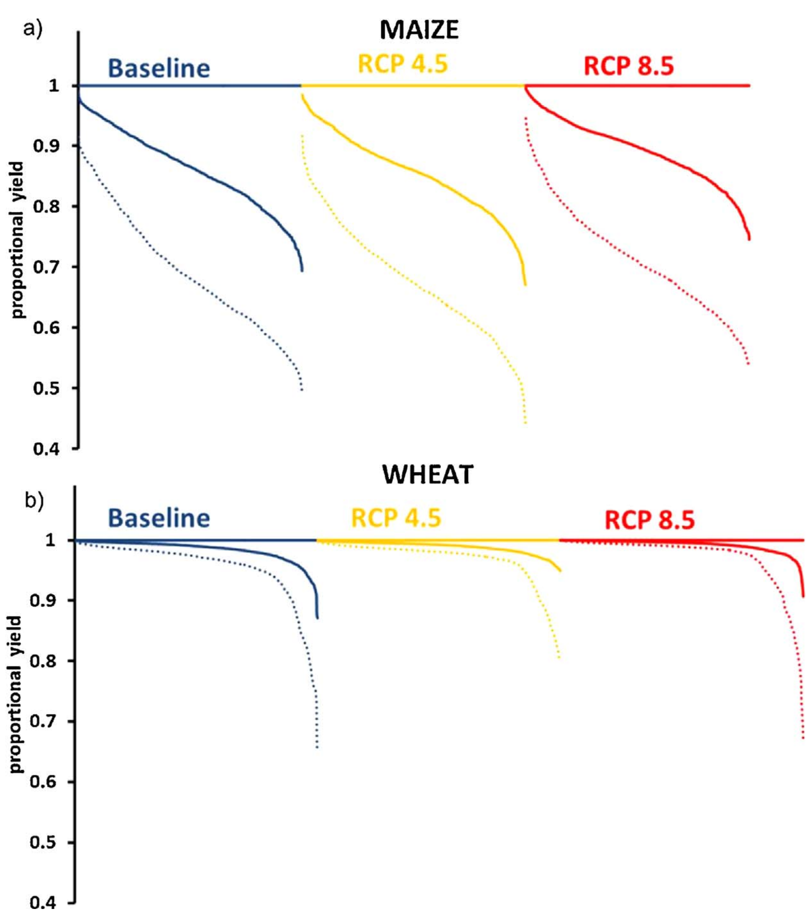

Fig. 6. Cumulative density curves of proportional yields calculated using Eq. (2), respect to the potential yield for the baseline (blue lines), RCP 4.5 (yellow lines), RCP8.5 (red lines) and for soil S1 (full lines) and S2 (dotted lines) for (a) maize and (b) wheat. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

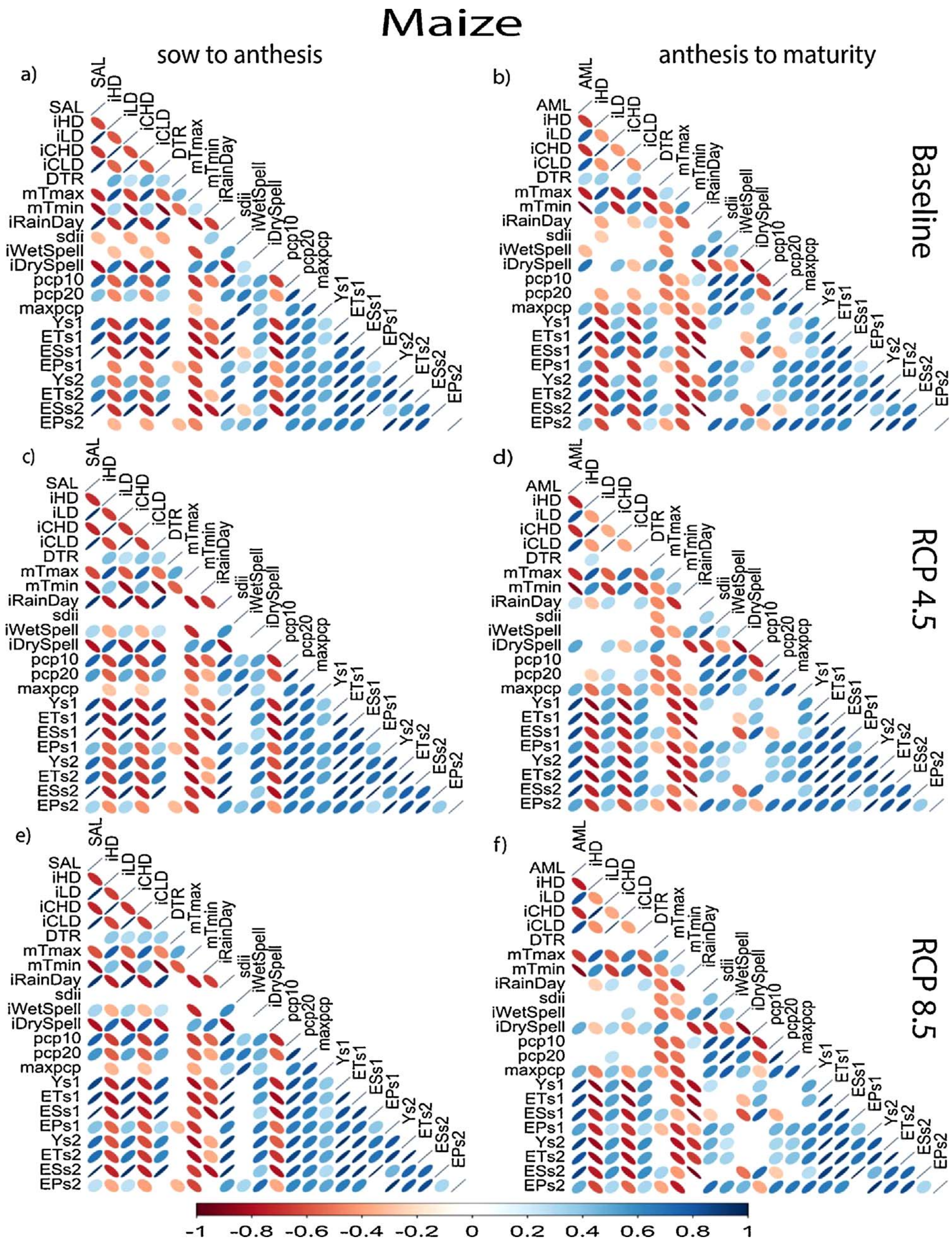

Fig. 7. Correlation plot between climate indices (Table 2) and maize simulated yield (Y_{xx}), water use (ET_{xx}), soil evaporation (ES_{xx}), plant transpiration (EP_{xx}), for soil the silty-clay soil (S1), and the sandy soil (S2), for the baseline, RCP4.5, and RCP8.5. The gradient of legend's colour is function of the strength of the correlation; while the slope of the ellipse indicated a negative or positive correlation (i.e. towards the right it is a positive correlation, and towards the left it is negative correlation). The shape of the ellipse indicated the strength of the correlation; a "diffuse" shape indicated a weak correlation. The correlations with *p*-value > 0.01 were not displayed and the area was left blank.

From anthesis to maturity most of the correlations weakened, and for simulations under S1 there was a decrease of significant relationships (Fig. 8b). Under RCP4.5 and 8.5 $mT_{\max}$ was not negatively correlated with any simulated outputs; there was only some weak positive correlation with the simulated plant transpiration on S1 and all the simulated outputs from S2 (Fig. 8d and f).

4. Discussion

The warming trends and the precipitation patterns across the SE USA vary between winter and summer crops, with maize being more affected than wheat by climate extremes and projected climate. The small decadal variability among the 10 GCMs for the baseline weather data (Fig. 1) was expected. However, for projected climate the winter crops showed more variability among the GCMs than summer crops (Fig. 1). The decadal trend showed signs of warming across the SE USA that were higher for the RCP8.5 scenario than the RCP4.5 scenario, which means that under the high emission scenario, for the same time-slice the warming will be higher. Karmalkar and Bradley (2017) found that the threshold of 2 °C in the southeast USA is reached at a different time respect to the one reached globally. In this study, the results of the decadal trends are extrapolated to quantify when the threshold of 2 °C is reached separately for wheat (winter crop) and maize (summer crop). Karmalkar and Bradley (2017) reported that in the southeast the 2 °C increase occurred in 2040 and 2036 for RCP4.5 and RCP8.5, respectively. In this study we found that for maize the 2 °C was reached in 2066 for maize under RCP4.5 and in 2046 under RCP8.5. For wheat, the 2 °C target was reached in 2096 and 2076 under RCP4.5 and RCP8.5, respectively.

When water and N conditions are optimal the increase in mean growing season temperature caused a reduction of simulated maize yields for both historical and projected climate. It has been reported that in optimal conditions, in the south, maize yields would be reduced by 2.5% for a 0.8 °C temperature increase (Muchow et al., 1990). But, this estimate did not take into account the effects of temperature on assimilation rate or respiration, as well as the failures in grain-set as function of raising temperatures (Hatfield et al., 2011). Lobell and Field (2007) estimated a loss of 8.3% per 1 °C increase in temperature. In this

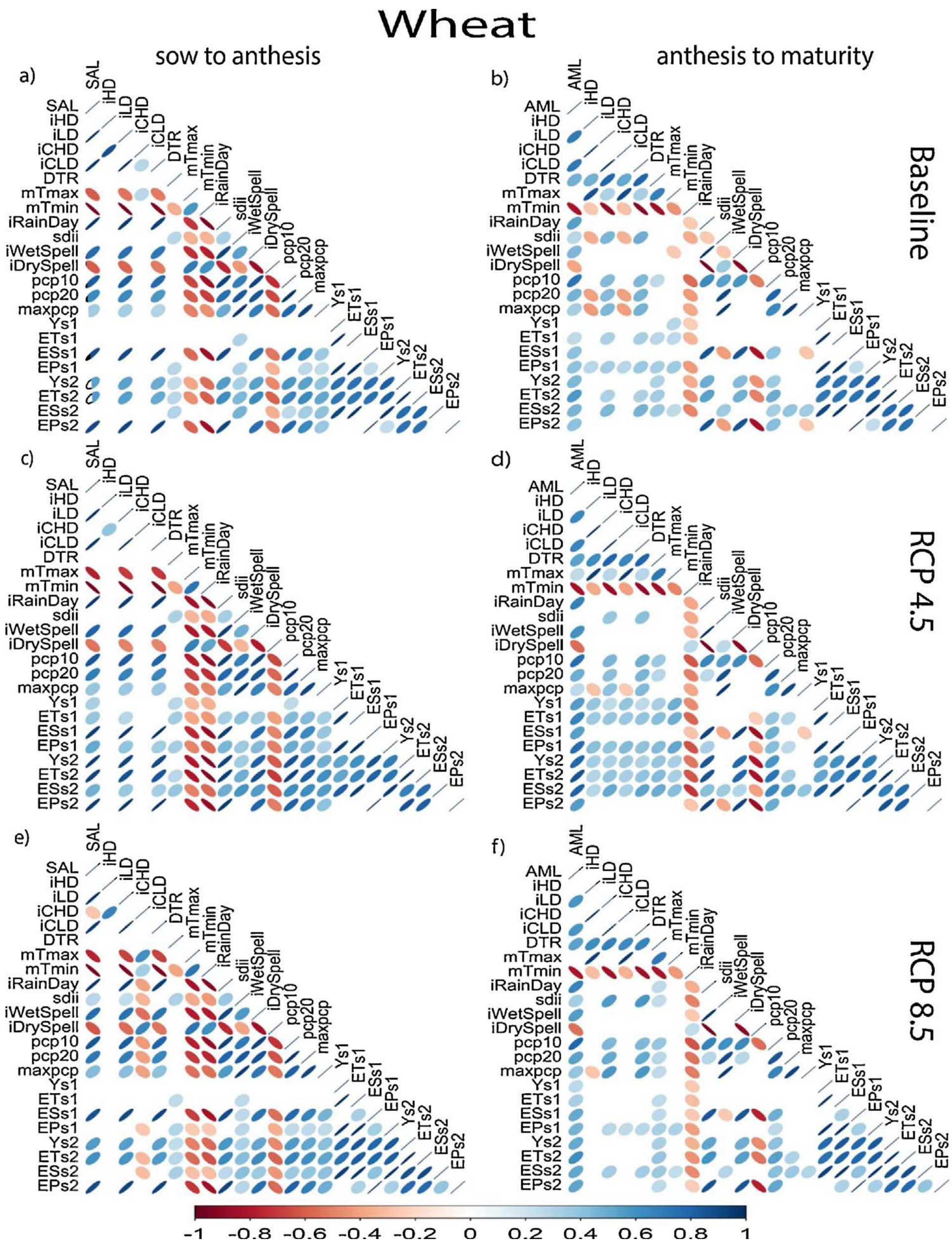

Fig. 8. Correlation plot between climate indices (Table 2) and maize simulated yield (Y_{xx}), water use (ET_{xx}), soil evaporation (ES_{xx}), plant transpiration (EP_{xx}), for soil the silty-clay soil (S1), and the sandy soil (S2), for the baseline, RCP4.5, and RCP8.5. The gradient of legend's colour is function of the strength of the correlation; while the slope of the ellipse indicated a negative or positive correlation (i.e. towards the right it is a positive correlation, and towards the left it is negative correlation). The shape of the ellipse indicated the strength of the correlation; a “diffuse” shape indicated a weak correlation. The correlations with p-value > 0.01 were not displayed and the area was left blank.

study, we found that 1 °C caused a decrease of 3.7% of yield for the baseline conditions, 4.6% for the RCP4.5 and 4.7% for the RCP8.5 (Fig. 2). For wheat the effects of temperature were less evident than maize. Wheat is mostly a winter grown crop and the mean growing season temperature is generally lower than the ones for maize. It has been reported that for each degree Celsius the estimated wheat yield losses will be 4–7%, depending on the scale of estimation, the methods, and the sites (Chowdhury and Wardlaw, 1978; Lawlor and Mitchell, 2000; Lobell and Field, 2007; Asseng et al., 2014). Some of these abovementioned studies considered crops exposed to mean air temperatures ranging between 15–30 °C, and for the same temperature range our simulated yield was only reduced by 2% for baseline, 3.8% for RCP4.5 and 3.2% for RCP8.5. This difference in estimated effects of temperature is due to the way the experiments or the modelling were conducted, at which scale and region the modelling was conducted, the data utilized, and which type of modelling approach was utilized.

It has been reported that the effects of CO_2 concentration on maize (from 380 to 450 ppm) would cause about 4% increase maize yield, but the combined effects of temperature and CO_2 would cause a decline of about −1.5% in yield in the Midwest (Hatfield et al., 2011). This estimate might be higher in the southeast where projected summer temperature will increase more. Hatfield et al. (2011) concluded that it is not possible to draw too many conclusions by such findings because of the limited number of studies where temperature and CO_2 interactions were analysed. On the other hand, wheat showed an increase of about 2.4% under interacting temperature and CO_2 concentrations (Hatfield et al., 2011). In this study we found that the simulated maize decreased from 350 to 936 ppm and wheat yield increased from the same CO_2 intervals. There is little variability among GCMs for the baseline simulations but such variability is high for maize at RCP4.5 and 8.5 than for wheat (Fig. 3).

The GCMs also differed in the way they projected growing season precipitations (Fig. 4). In fact, while for the baseline of both maize and wheat all the GCMs showed little variability, at RCP4.5 and 8.5 the variability increased and the difference between GCMs was between 50–150 mm of growing season rainfall (Fig. 4).

The different soil type made an impact in the simulated yield for wheat and maize under non-optimal conditions of water supply.

Overall, soil type had little impact on the winter crop; this is because wheat received enough rainfall for most of the simulated growing season to offset the soil characteristics. However, when rainfall was not adequate, the simulated yields on sandy soil (S2) were reduced to only 60% of the potential yield, while the silty-clay (S1) soil showed less reduction (Fig. 6). Maize, which is a summer crop and therefore more demanding in terms of water showed for both soil significant differences respect to the potential situations, but the general pattern is similar to the wheat, where sandy soil is the one causing lower yields.

The effects of increased CO_2 concentration only caused positive changes on crop water use, but the increase in canopy and leaf temperature and the increase in LAI caused by the enrichment of the CO_2 creates negligible changes of water use (Hui et al., 2001; Allen et al., 2003). Kimball (2010) reported that on wheat there would be about 8% decrease in water use under ample nitrogen and water conditions. In this study, given that nitrogen was always non-limiting and water stress varied according to the soil type used we found an average decrease of water use of 2.7% on S1 independently of the crop but a decrease of 4% on maize on S2 and 1.7% on wheat on S2. This might be due to the different soil characteristics in terms of water balance and how it would affect the plant transpiration (Fig. 5).

The relationship between simulated outputs and climate indices showed that maize was more sensitive to the number of days when air temperatures were above or below the threshold at which maize development is affected. These temperatures were $T_{min} < 8$ °C and $T_{max} > 34$ °C and affect maize development and yield, especially because these higher temperatures. Cammarano et al. (2016) found, using historical climate data that these extremes were mostly affecting maize between anthesis to maturity. This study analysed the period from sowing to anthesis and anthesis to maturity and found that both stages were negatively correlated with these thresholds. On the other hand, periods of no rainfall (dry spells) were more detrimental during the vegetative stage, when crop biomass growth is within the exponential phase and a high demand of nutrient and water is needed from the soil; this behaviour was also observed for the wheat (Figs. 7 and 8). Wheat was more sensitive to the absolute values of the highest T_{max} and the lowest T_{min} recorded rather than the number of days above the temperature thresholds.

In this study, only two contrasting soil types were used across the whole 110 point-based stations, rather than using the site-specific soil. The reason for doing so is to analyse, under each weather station, how the soil type would affect the water use and the simulated yield. With site-specific soil there would have been 110 single response to rainfall and it would have been much harder to separate the effect of a given soil type. Also, the uncertainty of the daily weather of the 10 GCMs would be better quantified if the soil is uniform across all the stations. The silty-clay soil was able to buffer the intra- and inter-annual variability or growing season rainfall because held more water than the sandy soil which would be utilized by the crop during periods of low rainfall.

5. Conclusions

This study analysed the effects of projected climate and climate extremes on a winter and summer crop in the southeast USA. The differentiation between winter and summer crops allowed quantifying the impact of temperature and rainfall separately rather than giving a single estimate of what would happen in the southeast USA. Maize yield (summer crop) is more susceptible than wheat yield (winter crop) to the changes in rainfall and temperature. For each 1 °C the simulated maize yield would decrease by 4.6% across the different climate projections, while wheat would be reduced by 3.8%. The use of two contrasting soil types helped to quantify how the simulated crop response to climate is influenced by soil type. The silty-clay soil showed a greater ability to withstand changes in temperature and rainfall than the sandy soil. Water use efficiency decreased under future projections by 2.7% on a silty-clay soil, independently of the winter/summer crop, but on a sandy soil the decrease was 4% for maize and 1.7% for wheat.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agrformet.2017.09.007.

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